ISSN 2319 - 5975
Volume 8, No.3, April - May 2019
International Journal of Networks and Systems
Available Online at http://www.warse.org/IJNS/static/pdf/file/ijns03832019.pdf
https://doi.org/10.30534/ijns/2019/03832019

A Personalized Course Recommender System for E-Learning

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ABSTRACT

In recent years, the internet has witnessed an aggressive growth in the amount of learning resources. This explosion of learning resources on the internet results in expanded interest for online learning resources by learners in e-learning environment. With this expansion of online learning resources, learners are experiencing challenges in deciding learning resources that are valuable and significant to their learning needs. Recommender systems can overcome this issue by filtering out inappropriate learning resources and automatically recommending suitable resources to the learners according to their interests. In this paper we are focusing on a course recommender system in an e-learning platform which tries to intelligently recommend courses to the learners based on their interest. This recommendation approach is used to provide learners some suggestions when they have trouble in choosing correct courses. It also allows us to study the behavior of learner regarding their course selection and suggests the best combination of courses in which the learners are interested.

Key words: Course recommender system, E-learning, Recommendation approach.

1. INTRODUCTION

Recommender systems are used in a variety of areas including movies, books, research articles, news, music, products in general etc. This paper focuses on a course recommender system in e-learning platform. E-learning means electronically learning and teaching process [1]. Today the internet has witnessed a significant growth in the use of online learning resources by learners. This explosion of learning resources on the internet results in expanded interest for online learning resources by learners in e-learning environment. Due to the information overload problem many learners are experiencing challenges in finding relevant courses. To overcome this issue course recommender system is proposed. Recommender systems can overcome this issue by filtering out inappropriate learning resources and automatically recommending suitable resources to the learners according to their interests. A course recommender system in an e-learning platform intelligently recommends courses to learners based on their interest. Recommendation seeker can be considered as the learner in the e-learning domain. This recommendation approach is used to provide learners some suggestions when they have trouble in choosing correct courses. It also allows us to study the behavior of learner regarding their course selection and suggests the best combination of courses in which the learners are interested in.

2. LITERATURE REVIEW

In paper [2], the authors proposed one of the widely implemented recommendation techniques. It is based on the assumption that “similar users have same preferences”. This technique aggregate rating of learning resources to recognize commonalities between learners and provide new recommendations based on inter-learner comparisons. A learner profile contains a vector of learning resources and their ratings. Ratings indicate the degree of preference. Two classes of collaborative recommendation are Memory-based and Model-based. The main disadvantage of this method is the cold start problem and rating sparsity problem. Cold start problem is mainly based on new user or new item. The new user problem occurs when there is a new learner to the system has no prior rating found in the rating table. So it is difficult to give prediction of a learning object for the new learner because it requires the learner’s historic rating to calculate the similarity for determining the neighbors. New item cold start problem occurs when there is no enough previous rating related to that learning object exists [3]. Rating sparsity problem occurs where the number of learners who have rated learning object is too small compared to the number of available learning objects. If there is no such overlap in ratings with the target learner occurs, it is difficult to generate appropriate recommendation [4].

In paper [5], the authors proposed a technique that works on the basis of comparison of the content of a learning objects and a learner profile. The two classes of content based recommendation are Case based reasoning techniques and Attribute-based techniques. It recommends only the learning objects that are in higher correlation with the learner profile or interest. The limitation of this recommendation is that it is static in nature and is not able to understand from the behavior of the network. The main limitation of this approach is over specialization. It lacks in suggesting diverse learning objects [6].The learners are recommended with learning objects that are already familiar with. It prevents learners from finding new learning objects and other alternatives.

The work [7] aims to classify the learners based on their personal attributes and the recommendations are based on the demographic classes. This approach is based on the hypothesis that all learners belonging to a certain demographic class have alike preference. Privacy is one of the big issues faced by this approach. In order to provide more accurate recommendation to the learner, the most sensitive data of a learner must be acquired.

The research [8] aim is to combine two or more different recommendation approaches. Depending on the area and characteristics of data, several hybridization methods are possible integrate recommendation techniques which may produce different outputs.

This work [9] focuses on systems that include additional information about learner's context which can be used to change recommendations based on contextual information such as location, available time, people nearby, etc. Contextual data can be used to classify the situation of an entity. The context data consists of different attributes, like physical location, date, season, emotional state, physiological state, personal history etc. It was integrated to improve the existing learner request response pattern that requires the learners to raise the wish for recommendation. It is necessary to combine the context data into the recommender systems so as to recommend learning objects to the learners under some circumstances.

The goal of research [10] is to propose objects based on a learner needs and preferences. It contains knowledge about how a specific learning object meets a specific learner need. The learner profile can be any knowledge structure that supports this conclusion. This technique collects knowledge about the learners and learning objects to apply them in to the recommendation activity. It is independent on learner ratings. It does not collect data about a specific learner because its intuition is independent of individual preferences. The main limitation of this approach is the requirement of knowledge acquisition.

In [11] a Fuzzy-based recommender system is proposed, which refers to a system where recommendations to users are generated on the basis of uncertain or vague information in many practical situations, users express their preference for items in linguistic terms such as 'very interested' or 'not interested'.

3. EXISTING SYSTEM

The existing course recommender system is illustrated in figure1 which is based on collaborative filtering.

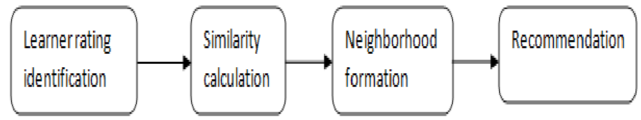

Figure 1: The existing system

It recommends the target learner learning resources that other similar learners liked in the past. The similarity of two learners can be calculated based on the similarity in their rating history [3]. Existing e-learning recommender system suffers from cold-start and data sparsity problems which limit their performance. The cold-start problem occurs due to an initial lack of ratings for new learner who have not rated any learning resource or new learning resource which have not been rated by any learner; hence it becomes impossible to make accurate recommendations. On the other hand, sparsity problem occurs where the number of learners who have rated learning resource is too small compared to the number of learning resources, hence the recommender system cannot generate any recommendations if there is no overlap in ratings occurs. Furthermore, collaborative filtering its own is not suitable for e-learning context.

4. PROPOSED SYSTEM ARCHITECTURE

In this paper we are proposing a model that overcomes the limitations in existing course recommender system. The architecture of the proposed system is illustrated in figure 2.

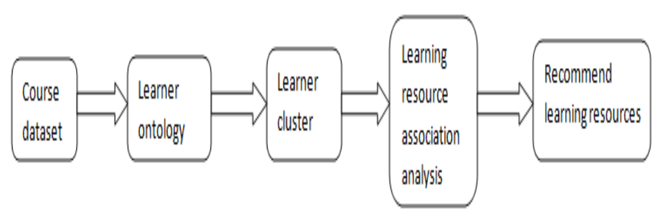

Figure 2: The proposed system

The proposed architecture describes a course recommender system based on ontology, clustering and association rule mining.

4.1 Learner Ontology

The ontology based recommender system improves the quality of personalization in recommendation systems. By incorporating ontology into the course recommender system we can provide more accurate recommendation of courses to the learners according to their personal preference and interests. Ontology is a conceptualization that consists of entity, attribute and relationships [3]. The learner ontology consists of learner preferences, learning style and their knowledge level. Sample learner ontology is illustrated in figure3.

4.2 Learner Cluster

In this module the knowledge level from the learner ontology is used by the clustering algorithm. It is used to cluster the learners based on their knowledge level. K-means algorithm is one of the most commonly used clustering algorithms. It is used to classify the dataset, provided the number of clusters is given in prior. By applying k means algorithm, three classes of knowledge levels namely beginner, intermediate and advanced is obtained. These three clusters are then used in the next step.

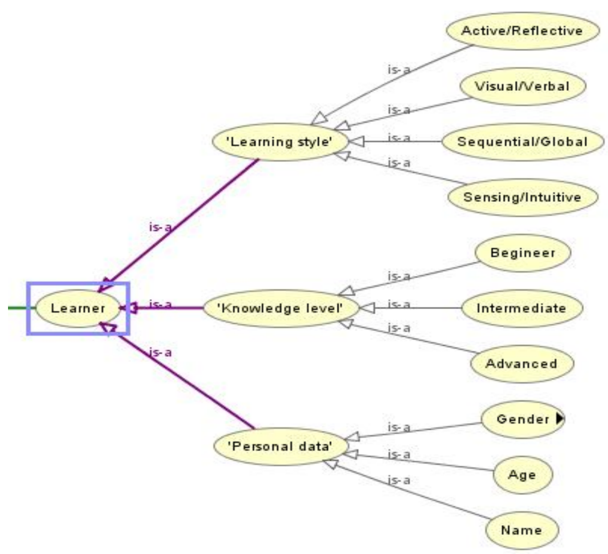

Figure 3: Sample learner ontology

4.3 Resource Association Analysis

In this step course mining is applied in to the clusters to generate final recommendation of courses. For generating course association rules we use apriori association algorithm. Association rule mines the accessing behavior of the learners to find the course association relationship in each cluster.. Confidence, support and lift are the three fundamental quality heuristics that are used to measure the interestingness of the association rule. The rules that have confidence and support greater than the user specified minimum confidence and minimum support are known to be interesting rules. To obtain course association rules, courses dataset is built by mapping each course to each learner in a transaction. In this model, instead of identifying learners whose tastes are similar to that of a given learner, we can use overlaps of other learners' tastes to match the given learner's taste.

By combining ontology, clustering and association rule mining, the cold start and data sparsity issues in the existing course recommender system can be solved. The new learner cold start problem can be overcome using the ontological knowledge level clustering approach. That is the new learner can be classified into one of the existing knowledge level cluster. Also by generating course association relationship in each cluster the data sparsity issue can be solved.

5. CONCLUSION

In this paper we are focusing on a course recommender system in an e-learning platform which tries to intelligently recommend courses to the learners based on their interest. This recommendation approach is used to provide learners some suggestions when they have trouble in choosing correct courses. By combining ontology, clustering algorithm and association algorithm, the proposed recommender system can overcome the limitations of existing systems and recommend appropriate courses more easily and effectively. The proposed system is still in its initial stage and more work needs to be done in future. The future work will focuses on to make a more useful automatically learner customized course recommender system.

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